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Capacitated Vehicle Routing Problem with Delivery Options: Private or Shared Location

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Abstract. Last-mile delivery costs are increasingly growing due to the rapid growth in E-commerce and the proliferation of online shopping especially after COVID-19 crisis. Integrating shared location delivery systems with home delivery has been a new trend in tackling last mile delivery challenges. This paper studies the Capacitated Vehicle Routing Problem with Delivery Options (CVRPDO). In this problem, customers can choose between picking up their requests from a shared location or receiving them at their homes within a preferred time window. The problem is formulated mathematically to minimize the total delivery costs considering the customers' preferences. Results include comparisons between delivery costs in the standard Capacitated Vehicle Routing Problem (CVRP) and those in the CVRPDO. Results demonstrate that the CVRPDO outperforms the CVRP by a considerable margin for varied-size instances providing a justification for substantial investment in establishing shared locations for delivery.

Keywords. Last-mile delivery, home delivery, shared locations pickup

1. Introduction

Delivery and logistics represent the most significant expenditure in the E-commerce sector, which impact online purchases. The considerable recent rise in E-commerce intensified the decision-making challenges in last-mile logistics [1]. The standard Vehicle Routing Problem (VRP) is one of the most prevalent problems in city logistics [2]. Consequently, companies must explore efficient solutions considering several dimensions, such as cost-effectiveness, customer satisfaction, delivery options, and sustainability to address the challenges of last-mile delivery problems [3].

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In the classic VRP customers' requests are delivered directly to a predetermined place, e.g. their home or work. This delivery option is costly and time-consuming [4]. In contrast, other options are considered in the Vehicle Routing Problem with Delivery Options (VRPDO). One of these options is that some customers pick up their requests from Shared Delivery Locations (SDL) [5]. SDLs, such as digital locker terminals, are generally located in places that open around the day, e.g., supermarkets and railway stations [4]. In this situation, some shipments could be delivered to SDLs instead of directly to the customers. This delivery option is more efficient and reduces the delivery failure rate [6]. Due to the provided customers' flexibility in time and preferred shared locations to pick up their packages, satisfaction levels improve considerably.

This paper considers a Capacitated Vehicle Routing Problem with Delivery Options (CVRPDO), a variant of the VRPDO which represents one of the most recent trends in the last-mile delivery problem [6]. The two key benefits of VRPDO over home delivery are eliminating unsuccessful deliveries due to no one being at home at the delivery time and decreasing the travel distance per delivery [7]. The VRPDO considers three types of customers:

- Customers who require delivery at their home location (HDC);
- Customers who elect to pick up their items from a shared location (ShLC); and
- Flexible customers who accept the two options of home delivery or shared location pickup (FlexC).

The CVRPDO is also an extension of the Vehicle Routing Problem with Time Windows (VRPTW) by incorporating two additional real-world aspects. Firstly, customers can select multiple pickup options (time windows) with different priorities, increasing their satisfaction. Secondly, some delivery options may share common locations, e.g., postal boxes [8].

In the CVRPDO problem, some customers may select only one delivery option (home delivery or shared location pickup). Others who have no preference between the two options can profit from this as the transportation company is allowed to decide the most beneficial option according to routing schedules, with compensation to the customers who will pick up their requests from one of the SDLs. In this problem, a cost minimization objective and customer satisfaction constraints are considered [9].

The objective of this paper is to propose a Mixed Integer Linear Programming (MILP) model for the CVRPDO showing how vehicle capacity constraints can be incorporated into a VRPDO model.

The remainder of the paper is structured as follows: section ***II***, describes the literature review of the problem. In section ***III***, the problem definition is introduced. The mathematical model is formulated in section ***IV***. Section ***V*** presents and compares the results of the computational study. Conclusions are drawn in section ***VI***.

2. Literature Review

The VRPDO and the CVRPDO are NP-hard problems as they are extensions of the VRP [10]. Due to its recent emergence, few studies in the literature tackled the VRPDO. However, its importance has been highlighted by the significant growth in online shopping and E-commerce during and after the COVID-19 pandemic [11].

To the best of the authors' knowledge, the first mention of VRPDO was in 2005 [10], where Furmans et al. modelled the VRPDO as a mixed integer program. They proposed a solution based on a branch and price approach using a decomposition scheme. Optimal route selection was performed using linear programming, while constraint programming was used for modelling and calculating optimal vehicle routes with side constraints. Johan Los et al. [12] studied the pickup and delivery problem with shared locations and various preferences. The problem was solved with an Adaptive Large Neighborhood Search metaheuristic (ALNS). Results from that metaheuristic were compared with a commercial solver's computed results.

As in the Generalized Vehicle Routing Problem with Time Windows (GVRPTW) [13, 14], customer requests in the VRPDO can be delivered at different locations. The VRPDO is the general case of GVRPTW, as the latter considers a single preference without shared location options. In 2020, Yuan et al. [14] proposed a branch and cut algorithm to solve instances of the single vehicle GVRPTW with up to 30 node clusters. Moccia et al. (2012) [13] applied a tabu search algorithm to solve large instances with up to 120 clusters within a few minutes.

As a result of tight time windows and high operational costs in last-mile delivery systems, an alternative, such as the Vehicle Routing Problem with Home and Roaming Delivery Locations (VRP(H)RDL), was considered. The VRP(H)RDL is a variant of the GVRPTW and a particular case of the VRPDO [15]. Lombard et al. [16], Sampaio Oliveira et al. [17] and, He et al. [18] considered the VRP(H)RDL with stochastic travel times. In these papers, a variant of the VRPRDLs is considered where a parcel could be delivered to the trunk of the customer's vehicle, which can be in various locations within the day.

Another method to reduce failure in the last mile delivery is to apply different time windows with different locations for each customer. Sadati M et al. [19] proposed the Electric Vehicle Routing Problem with Flexible Deliveries (EVRP-FD). The objective was to minimize travel time and the number of vehicles, and customers could select multiple delivery locations with corresponding time windows. A. Estrada-Moreno et al. [20] examined feasibility deliveries by having different constructive time windows, for example, the days of the week. The aim is to minimize the distribution costs and the penalty paid for flexible delivery.

Tilk et al. [6] implemented a branch-and-price-and-cut algorithm to solve the VRPDO problem exactly. In this paper, customers may have different delivery priorities, and for each delivery option, customers define a different time window during the purchasing process. The objective of VRPDO is to minimize the total cost without neglecting customer priorities.

In 2021, S. Mancini and M. Gansterer [9] proposed a hybrid delivery system that considers all customers to be flexible to receive their request within the time window at their home or pick it up from a shared location. A penalty would be paid to customers who would pick up their goods from SDLs as compensation. Although Mancini et al. solved the VRPDO with MIP and solved most instances optimally, they did not consider factors such as the vehicles' capacity and available vehicle number.

Compared with the literature, the main research contribution of this work is adding capacitated vehicle constraints in VRP last mile with private and shared locations delivery options, with compensation to FlexC, who will pick up their requests from SDLs. Also, varying vehicle capacities are examined. To the best of the authors' knowledge, none of these issues have been addressed in the literature.

3. Problem Definition

The CVRPDO can be defined as follows: let I represent the number of customers (number of requests). All delivery routes start at the depot (0), F the set of all delivery locations, and I_1, I_2, and I_3 are the sets of different types of customers (HDC, ShLC, and FlexC, respectively). Each request must be delivered to a private location of a customer (i) or SDL (f), and the customer (i) can pick it up at any time. Customers are assigned to a subset of SDLs which are no more than 5 km apart from this customer (i.e. $V_i \subseteq F$).

Each SDL f has a limited number of requests B_f (depending on the number and the size of empty lockers in the SDL). A service time s_i is considered for each request. In this paper, the size of the lockers is ignored, each customer has only one request, and the service time at SDL is fixed and independent of any factors, such as the number of handled parcels. While the size of lockers is ignored, the size of any parcel (Sp) is considered only when vehicles' capacity are examined.

A time window $[Ei, Li]$ is available to visit customer i ($i \in I$) in their private location; this time is determined previously during the purchasing process. This time window is applied for home delivery requests as a guarantee of the customer being available at this time to receive their orders to reduce failed deliveries. On the other hand, SDL deliveries are not restricted by a time window, as customers have the freedom to get their requests at any time.

The following sets of nodes can be defined in the network: $N = I \cup F$ and $N_O = N \cup 0$. For requests i and j ($i, j \in I$), their private locations are represented as nodes i and j, respectively. Travel costs C_{ij} and travel times t_{ij} are proportional to the travel Euclidean distance d_{ij}, for each couple of nodes i and j in N_O. Each tour starts and ends at the depot within a period between $[0, T_{max}]$; moreover, it incurs a fixed cost denoted as (γ). Compensation (δ) is paid to FlexC if they are not visited directly by a vehicle in their private location. The number of available vehicles is ($Num.V$).

The model's objective is to minimize the total distribution cost, which is the sum of three cost elements: travel cost, vehicle utilization cost, and the penalty or compensations (δ). In this model, each customer or SDLs can be visited by only one vehicle. *Fig.* ***1*** depicts an example of last-mile delivery with three different customer types (i) ShLC, (ii) FlexC and (iii) HDC for a small instance with four customers and one SDL. Travel costs are calculated proportionally to travel distance d_{ij} between two nodes i and j. Vehicle usage cost and compensation for customers picking up their items from SDL are assumed to be 1 and 5, respectively.

4. Mathematical Model

For the mathematical formulation, the following decision variables are assigned:

- X_{ij}: binary variable indicating whether j is visited directly after node i
- Y_{if}: binary variable indicating whether i is delivered to SDL f
- Z_f: binary variable indicating whether SDL f is visited
- T_i: non-negative variable indicating the visit time at node i
- u_i: non-negative variable tracking the total load of a vehicle when it arrives at node $i \in N$
- q_i: non-negative variable determining the amount that must be delivered to customers or SDL $i \in N$

The mathematical formulation is reported in the following:

$$\text{Min} \sum_{i\in N_0}\sum_{j\in N_0} c_{ij}X_{ij} + \delta\sum_{i\in I_3}\sum_{f\in F} c_{if}Y_{if} + \gamma\sum_{n\in N} X_{0n} \quad (1)$$

$$\sum_{i\in N_0} X_{ij} + \sum_{f\in V(j)} Y_{jf} = 1 \qquad \forall j \in I \quad (2)$$

$$\sum_{i\in N_0} X_{ij} = \sum_{i\in N_0} X_{ji} \qquad \forall j \in N_0 \quad (3)$$

$$Z_f \geq \frac{1}{|I|}\sum_{i\in I} Y_{if} \qquad \forall f \in F \quad (4)$$

$$\sum_{i\in N_0} X_{if} = Z_f \qquad \forall f \in F \quad (5)$$

$$T_j \geq T_i + t_{ij} + s_j - 2T_{\max}(1 - X_{ij}) \qquad \forall j \in N \quad \forall i \in N_0 \quad (6)$$

$$-T_{\max}\sum_{f\in F} Y_{if} + E_i \leq T_i \leq +L_i + T_{\max}\sum_{f\in F} Y_{if} \qquad \forall i \in I \quad (7)$$

$$T_j + s_j + X_{j0}t_{j0} + X_{jf}t_{jf} \leq T_{\max} \qquad \forall j \in N \quad \forall f \in F \quad (8)$$

$$\sum_{i\in I} Y_{if} \leq B_f \qquad \forall f \in F \quad (9)$$

$$Y_{if} = 0 \qquad \forall i \in I \quad \forall f \in F: f \notin V_i \quad (10)$$

$$\sum_{j\in N} X_{0j} \leq \text{Num.V} \quad (11)$$

$$\sum_{f\in F} Y_{if} = 0 \qquad \forall i \in I_1 \quad (12)$$

$$\sum_{f\in F} Y_{if} = 1 \qquad \forall i \in I_2 \quad (13)$$

$$q_i = \begin{cases} Sp_i & \forall i \in I \\ \sum_{i\in I} Y_{if} Sp_i & \forall f \in F \end{cases} \quad (14)$$

$$\text{if } x_{ij} = 1 \Rightarrow u_i + q_j = u_j \qquad \forall i,j \in N: i \neq j \quad (15)$$

$$q_i \leq u_i \leq Q \qquad \forall i \in I \quad (16)$$

Constraints from 2 to 10 are adopted from S. Mancini and M. Gansterer's paper [9]. Constraints (2) ensure that each customer may receive their request at home or pick it up from a shared location within a 5km radius. Constraints (3) guarantee the continuity of each route. Constraints (4) and (5) control that if a shared location is opened, only one vehicle will visit it. Constraints (6) track the arrival time at different nodes. Constraints (7) organize that the customers be visited within the predetermined time window if they receive their request at home, but in the case of picking up their parcels from a SDL, there is no time limit. Constraints (8) ensure that the finishing time for each vehicle is less than Tmax. Constraints (9) deal with the number of requests assigned to each SDL to ensure that they do not exceed the capacity of this SDL, Bf. If the distance between any customer and SDL is more than 5km, the customer cannot use this SDL, which is constrained by constraints (10).

Constraints (11) keep utilized vehicles less than the available ones. Constraints (12) and (13) accomplish each customer's priorities. Constraints (14), (15), and (16) are for the capacity of the vehicles to control the utilization of the vehicle within the available limit.

5. Implementation and Results

The computational study contains comparing the MIP approach of CVRPDO against the standard CVRP with only a home delivery option. All computational experiments were conducted using data from Mancini and Gansterer [9].

Three sets of instances were examined with 5 SDLs and 25, 50, and 75 customers, respectively. Each customer is assumed to have only one request. The capacity of each

SDL is chosen as a fraction of the number of customers (5, 10, and 15 parcels). Ten vehicles are available with an initial capacity (Q) of 50 units for the first phase of the computational experiments, whereas a deep analysis is performed on the effect of the Q variation on solution quality in the second phase. The parcel size was assigned a random value between 1 and 10 units for each customer's request.

The distribution area is 10×10 km^2; the depot is in the middle south of the area, while SDLs are in the centre, the southeast, southwest, northeast and northwest. Each set of instances has ten instances. Sets are denoted as *I_X_Y*, where X and Y are the number of requests and instances, respectively.

A time horizon of 720 minutes is considered with 12 slots, 60 minutes for each slot. The travel cost between any two nodes, i and j, C_{ij}, is three times the distance between these nodes. The travel speed is 20 km/hr., which is standard in urban cities. The penalty (δ) for a customer i equals to the distance between the customer and the pickup node; and the fixed vehicle cost (γ) is selected as 1. The service time (s_i) is considered as 5 min for home delivery and 10 min for SDLs. Each customer could pick up their requests from SDLs located within a distance of 5 km (travel time radius of 15 minutes).

5.1. Comparing the MIP Approach of CVRPDO against the Standard CVRP

In this section of the computational study, comparisons between standard CVRP and CVRPDO are examined in Table **1**, Table **2**, and Table **3** for small, medium, and large instances, respectively. A maximum runtime limit of 1 hour or getting the optimal solution with a zero gap were selected as stopping criteria for the implementation.

The results show that solutions for all instance sets have significantly improved when adding delivery options to the model. The standard CVRP model gets the optimal solutions with zero gap values for most small and medium instances, while the CVRPDO models get the optimal values for most small instances. The CVRPDO model improves the solution by 38%, 32%, and 24% on average for small (Table **1*)*,** medium (Table **2**) and large (Table **3**) instances, respectively.

In the CVRPDO, optimal solutions were achieved for most small instances (Table **1**), except the *I_25_3* instance solved with a gap of 7%. All instances yield a gap to the optimal solution between 17% and 33% for medium instances (Table **2**) and 30% and 42% for large instances (Table **3**), with a runtime limit of 1 hour.

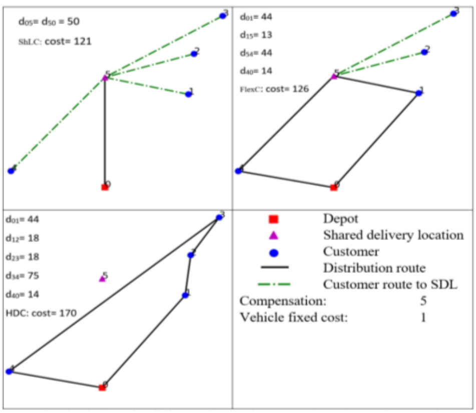

Figure 1. Optimal solutions for different distribution strategies: ShLC, FlexC, and HDC.

Table 1. Comparison of the MIP solution approach applied to small-sized instances (25 customers). The best-known solution, the optimality gap, and runtimes are reported.

Instance	Standard CVRP			CVRPDO			Percentage Reduction in Objective Value
	Gap (%)	*Time (s)*	*Objective Function*	*Gap (%)*	*Time (s)*	*Objective Function*	
I_25_1	0.00	3	265	0.00	836	147	44.69%
I_25_2	0.00	6	273	0.00	85	170	37.79%
I_25_3	0.00	3	246	0.07	3600	150	39.02%
I_25_4	0.00	6	256	0.00	9	157	38.58%
I_25_5	0.00	3	245	0.00	200	164	33.08%
I_25_6	0.00	3	250	0.00	748	166	33.70%
I_25_7	0.00	5	240	0.00	933	161	32.98%
I_25_8	0.00	7	298	0.00	46	173	41.93%
I_25_9	0.00	13	255	0.00	828	153	39.99%
I_25_10	0.00	7	248	0.00	294	162	34.79%
Avg. Reduction							38%

Table 2. Comparison of the MIP solution approach applied to medium-sized instances (50 customers). The best-known solution, the optimality gap, and runtimes are reported.

Instance	Standard CVRP			CVRPDO			Percentage Reduction in Objective Value
	Gap (%)	*Time (s)*	*Objective Function*	*Gap (%)*	*Time (s)*	*Objective Function*	
I_50_1	0.00	205	391	0.19	3600	263	33%
I_50_2	0.00	11	407	0.16	3601	261	36%
I_50_3	0.00	1453	439	0.33	3600	299	32%
I_50_4	0.00	32	402	0.19	3600	281	30%
I_50_5	0.02	3600	385	0.22	3600	272	29%
I_50_6	0.00	631	382	0.18	3600	275	28%
I_50_7	0.00	635	396	0.24	3600	243	39%
I_50_8	0.00	158	362	0.17	3600	253	30%
I_50_9	0.00	3600	403	0.24	3600	274	32%
I_50_10	0.00	85.18	410	0.27	3600	276	33%
Avg. Reduction							32%

Table 3. Comparison of the MIP solution approach applied to large-sized instances (75 customers). The best-known solution, the optimality gap, and runtimes are reported.

Instance	Standard CVRP			CVRPDO			Percentage Reduction in Objective Value
	Gap (%)	*Time (s)*	*Objective Function*	*Gap (%)*	*Time (s)*	*Objective Function*	
I_75_1	0.08	3600	499	0.39	3600	417	16%
I_75_2	0.00	2878	513	0.33	3600	352	31%
I_75_3	0.06	3600	512	0.37	3600	407	21%
I_75_4	0.09	3600	584	0.35	3600	400	32%
I_75_5	0.10	3600	588	0.42	3600	462	22%
I_75_6	0.12	3600	574	0.39	3600	447	22%
I_75_7	0.10	3600	567	0.37	3600	409	28%
I_75_8	0.07	3600	509	0.30	3600	408	20%
I_75_9	0.06	3600	517	0.35	3600	376	27%
I_75_10	0.06	3600	535	0.36	3600	422	21%
Avg. Reduction							24%

5.2. Comparison of Different Vehicles Capacities

For the computational tests introduced in Section *VI*, the vehicle capacity was assumed to be 50 units. To gain more insight into the impact of different vehicle types with various capabilities, three categories of vehicles were examined with capacities of 50, 70, and 90 units.

The runtime stopping criteria was selected as in the previous section: 1 hr or getting the optimal solution. Objective function values for using vehicles with a capacity of 70 or 90 (Q70 and Q90) were compared with the vehicle capacity of 50 (Q50). The objective function values of the three capacities for small, medium, and large instances were reported in *Fig. **2***, *Fig. **3***, and *Fig. **4***, respectively.

For instances with 25 customers (small instances) (*Fig. **2***), *Q70* and *Q90* vehicle utilization improved in most instances, with an average of 9% and 13% for *Q70* and *Q90*, respectively. On the other hand, for instant *I_25_1 Q50* vehicles were better than *Q70*.

For 50 customers (medium instances) (Fig. 3), Q70 and Q90 vehicles enhance all instances solutions. Compared to *Q50* vehicles, an average improvement with percentages 14 and 20 was observed when utilizing *Q70* and *Q90*, respectively.

For 75 customers (large instances) (*Fig. **4***), *Q70* and *Q90* vehicles usage improved all instances solutions. Compared with *Q50* vehicles, an average cost reduction with percentages 19 and 27 was achieved when selecting *Q70* and *Q90*, respectively. Whereas the maximum reduction in *Q70* vehicles is 22% at *I_75_6*, instance *I_75_5* get the maximum reduction when using *Q90* vehicles with 10.38%.

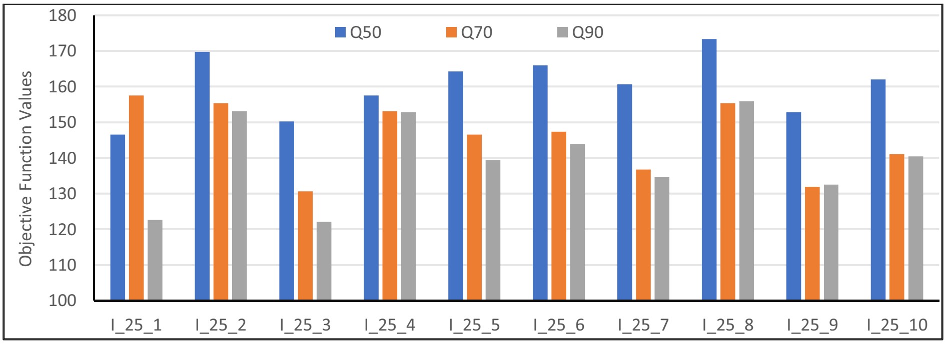

Figure 2. Comparison of three vehicle capacities (Q50, Q70, and Q90) applies to small-sized instances.

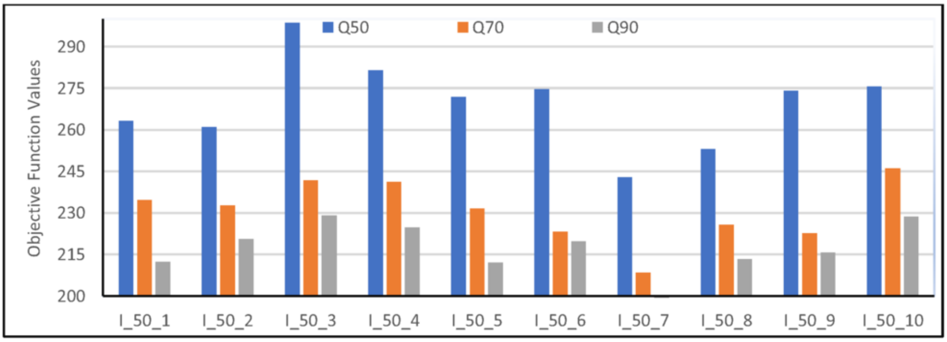

Figure 3. Comparison of three vehicle capacities (Q50, Q70, and Q90) applies to medium-sized instances.

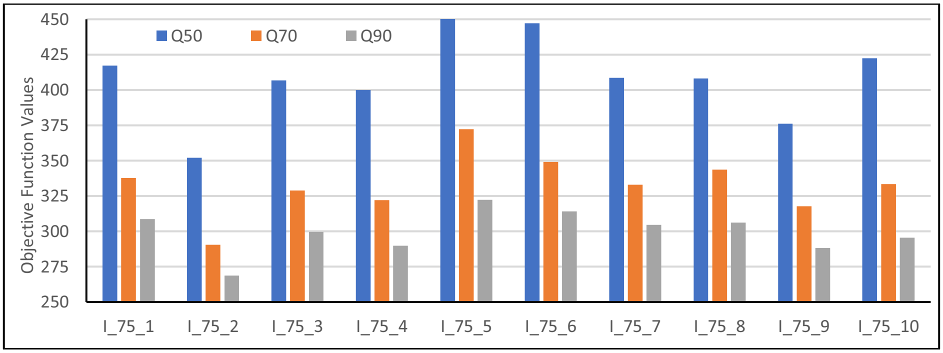

Figure 4. Comparison of three vehicle capacities (Q50, Q70, and Q90) applies to large-sized instances.

6. Conclusion

The considerable growth in E-commerce and online shopping and changing customers' lifestyles have led to an explosion inhome delivery request. Reducing costs in last-mile delivery has become a critical concern for logistics companies. The standard CVRP approaches consider a home delivery option without shared location usage, and this type of system exhibits inefficiencies in cost, time, and successful execution of deliveries. However, integrating the pickup option, which permits customers to prioritize between home delivery or collecting their requests from SDLs, increases service quality and reduces operating costs.

Accordingly, an approach that combines the standard CVRP with VRPDO is proposed. In this study, the CVRPDO was formulated mathematically within a minimization objective function that considers three types of costs: (i) travel distance cost, (ii) penalty cost and (iii) utilization vehicle fixed cost. In this model, two customer preferences are considered: (i) home delivery and (ii) picking items from SDL, and some customers are flexible with the two options. The flexible customers who will pick up their items from an SDL would be compensated by the transportation company (penalty cost). The capacity of the SDLs and vehicles are considered.

A computational study was performed to compare the solutions of the standard CVRP with CVRPDO. Moreover, the impact of different vehicle capacities was investigated. For most small instances, the MIP model gets optimal values. In some instances, especially medium and large instances, the 1-hour time limit included in the implementation was reached.

The results of studying the impact of various vehicles' capacities show improvement in most solutions when vehicles with higher capacities are used. The results proved that integrating delivery options to the standard approach improves the quality of solutions. The distribution costs dropped by an average of 38%, 32%, and 24% for small, medium, and large instances, respectively, while customers' preferences were still respected.

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